Data-Driven Prognostics Methods and Performance Evaluation

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Overview

Motivation

Develop data-driven algorithms for prognostics and demonstrate their applicability on diverse applications to benchmark prognostic performance.

- Evaluate different algorithms for their suitability for various applications
- Assess trade-offs that arise from
  - Amount of data needed
  - Computational complexity
  - Robustness towards input space perturbations
  - Ability to support uncertainty management
  - Accuracy and usability of predictions (prediction horizon)
- Develop performance evaluation metrics for prognostics

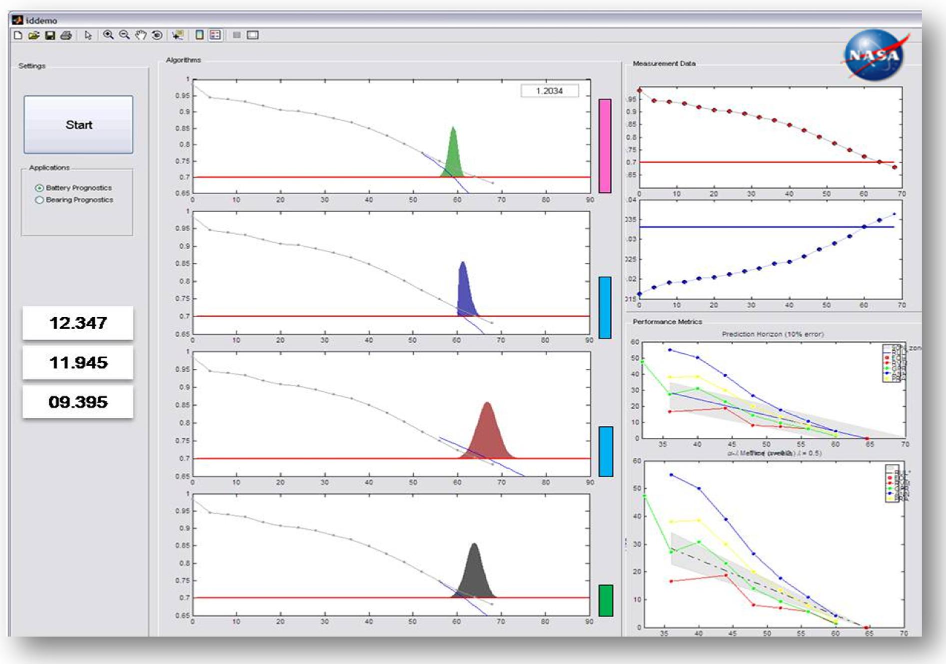
Forecasting Applications

- End-of-Life predictions
  - A prediction threshold exists
  - Use monotonic decay models
  - Event predictions — RUL Prediction
  - Decay predictions — Trajectory Prediction
  - No/Little history data — Aerospace, Nuclear — Model-based + Data-driven
  - History data — Statistics can be applied
    - Nominal & failure data — Medicine, Mechanical systems, structures
    - Nominal data only — Electronics, Aerospace
- Future behavior predictions
  - Non-monotonic models
  - No thresholds
  - Continuous predictions — Weather, Finance
  - Discrete predictions — Economics, Supply Chain
    - Qualitative — Increasing or decreasing trends
    - Quantitative — Predict numerical values

Algorithms should be developed to cater to specific prediction tasks

Software Demonstration

- Interactive software environment allows visual assessment in addition to numerical performance tracking.



Features

- Runs multiple prediction algorithms
- Tracks and compares prediction performance simultaneously
- Computes performance metrics

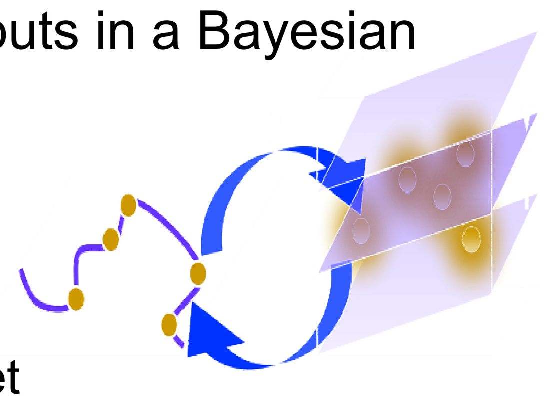
Algorithms

Relevance Vector Machines

- Supervised learning algorithm using expectation maximization
- Stochastic sparse kernel method similar to Support Vector Machines
- Allows probabilistic outputs in a Bayesian framework
  - Data

Targets
Observations

$$\mathbf{t}_n = F(\mathbf{x}_n;\mathbf{w}) + \varepsilon_n$$



  - Likelihood of the data set

Design matrix (kernel functions)

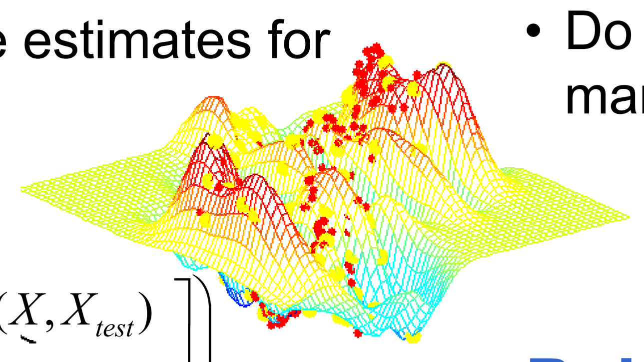
$$p(\mathbf{t}\mid\mathbf{w},\sigma^2) = (2\pi\sigma^2)^{-N/2}\exp\left\{-\frac{1}{2\sigma^2}\|\mathbf{t}-\Phi\mathbf{w}\|^2\right\}$$

  - Predictions for the new observations $\boldsymbol{x}^*$

$$p(\mathbf{t}^*\mid\mathbf{t}) = \int p(\mathbf{t}^*\mid\mathbf{w},\sigma_{MP}^2)\,p(\mathbf{w}\mid\mathbf{t},\eta_{MP},\sigma_{MP}^2)\,d\mathbf{w}.$$

Gaussian Process Regression

- Supervised learning belonging to the family of least squares estimation algorithms
- Bayesian framework to derive posteriors from priors (history data)
- Provides mean and variance estimates for the predictions
  - Prior



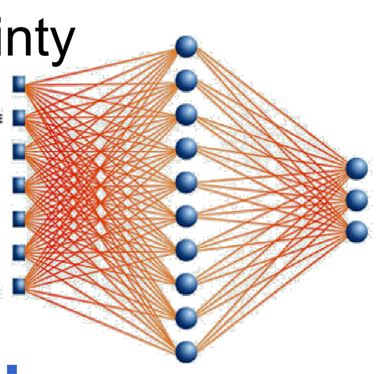
$$\begin{bmatrix} y \\ f_{test}\end{bmatrix} \sim N\left(0,\begin{bmatrix} K(X,X)+\sigma_n^2 & K(X,X_{test}) \\ K(X_{test},X) & K(X_{test},X_{test})\end{bmatrix}\right)$$

  - Posterior

$$f_{test}\mid X,y,X_{test} \sim N(\bar{f}_{test},\mathrm{cov}(f_{test})),\ \text{where}$$
$$\bar{f}_{test} \equiv \mathrm{E}[f_{test}\mid X,y,X_{test}] = K(X,X_{test})[K(X,X)+\sigma_n^2 I]^{-1}y,$$
$$\mathrm{cov}(f_{test}) = K(X_{test},X_{test}) - K(X_{test},X)+\sigma_n^2 I]^{-1}K(X,X_{test}).$$

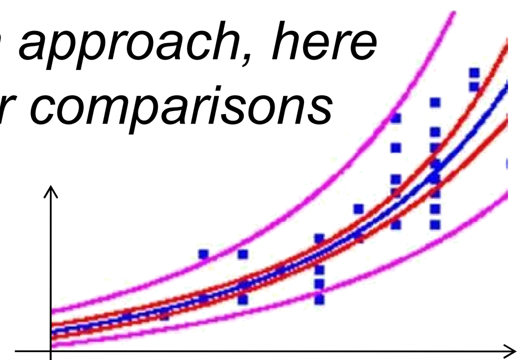
Artificial Neural Networks

- Universal function approximators
- Widely used for data-driven learning, i.e. provide a well represented prognostic technique, e.g. DWNN, CPNN
- Do not incorporate uncertainty management inherently



Polynomial Regression

A simple regression approach, here used as baseline for comparisons



Performance Evaluation

Key Issues

- Performance evaluation is key for prognostics technology maturation and deployment
  - A stringent performance evaluation is needed before prognostics can be used in critical fielded applications
    - e.g. a maintainer must trust a prediction before scheduling maintenance
  - Metrics help establish design requirements
  - Allow comparing different algorithms to establish application specific suitability
  - Provide feedback to help improve algorithms
- Lack of standardized methods for prognostic performance evaluation calls for new metrics customized for Prognostic Health Management scenarios
  - Need a better account of uncertainty management
  - Performance should improve as end-of-life approaches
  - Traditional metrics based on accuracy, precision, and robustness should be extended to suit prognostics

- Approach
  - A variety of metrics are under investigation and being used to evaluate different data-driven algorithms
  - New metrics are being developed and evaluated

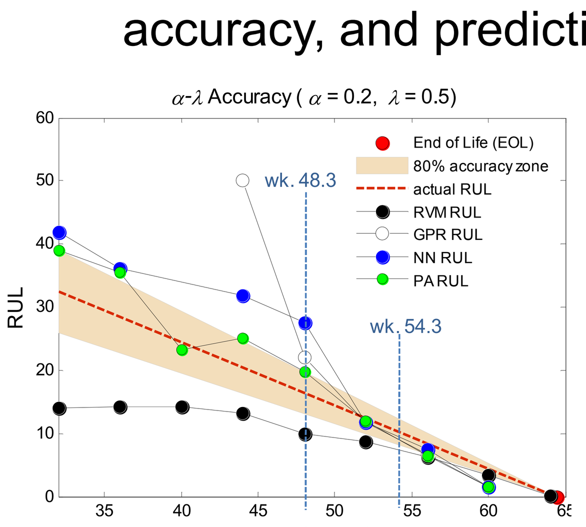
Performance Metrics

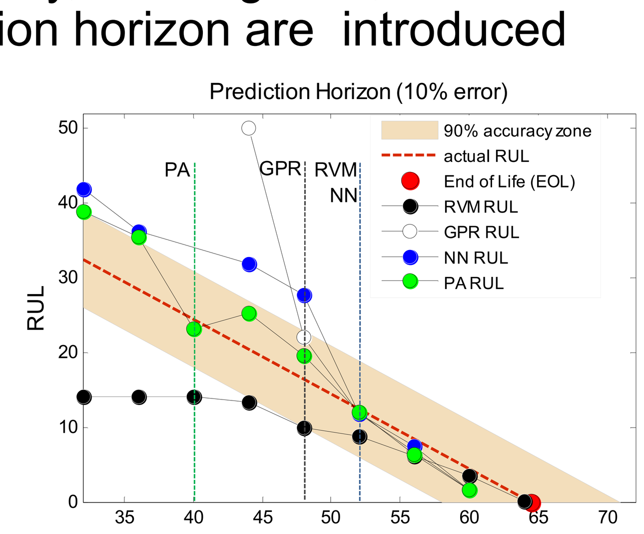
- Algorithm Performance
  - Accuracy
  - Robustness
  - Precision
  - Trajectory
- Computational Performance
- Cost-benefit

Metrics can be classified under several categories

Metrics

- A variety of performance metrics developed specifically for prognostics
  - New metrics track performance dynamics
  - Metrics like α-λ accuracy, convergence, relative accuracy, and prediction horizon are introduced





- A diverse set of prognostics applications are being used for benchmarking
  - NASA prognostics repository hosts variety of data sets with run-to-failure characteristics
    - http://ti.arc.nasa.gov/project/prognostic-data-repository/
  - Data sets include mechanical, electrical, electronics, and aerospace systems

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